

# Posterior consistency in Bayesian inference with exponential priors

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## The setting

$Y^{(n)} \sim P_{\theta}^n$ ,  $\theta$  living in  $(\Theta, d)$

- prior  $\mu$  on  $\Theta \longrightarrow$  posterior  $\mu(\cdot | Y^{(n)})$

Interested in asymptotic properties of  $\mu(\cdot | Y^{(n)})$  as  $n \rightarrow \infty$ , assuming

- $\exists$  an underlying truth  $\theta_0$
- as  $n \rightarrow \infty$ ,  $Y^{(n)}$  corresponds to infinitely-informative data limit

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Examples:

- White noise model:  $Y_t^{(n)} = \int_0^t w_0(s) ds + \frac{1}{\sqrt{n}} B_t$ ,  $t \in [0, 1]$ ,  
( $\Theta = L^2[0, 1]$ )
- Density estimation:  $Y_1, \dots, Y_n \stackrel{\text{i.i.d.}}{\sim} \pi_0$ ,  $\pi_0(x) = \frac{e^{w_0(x)}}{\int_0^1 e^{w_0(y)} dy}$   
( $\Theta = C[0, 1]$ )

## Consistency with contraction rates

$\mu(\cdot | Y^{(n)})$  is said to contract with rate  $\epsilon_n$  wrt  $d$  at  $\theta_0$  if

$$\mu\left(\theta : d(\theta, \theta_0) \geq C\epsilon_n | Y^{(n)}\right) \rightarrow 0 \text{ in } P_{\theta_0}^n\text{-probability}$$

*Ghosal & van der Vaart 2007:*

Conditions on prior

- $\mu$  puts sufficient mass around  $w_0$ ,
- $\exists \Theta_n \subset \Theta$  with ‘*bounded complexity*’ and  $\mu(\Theta_n \setminus \Theta)$  sufficiently small

model:  $\exists$  statistical tests distinguishing  $\theta_0, \theta_1$  with error probabilities exponentially small in  $d(\theta_0, \theta_1)$

satisfied by white noise and density estimation models

## General contraction for white noise model

$$Y_t^{(n)} = \int_0^t w_0(s) ds + \frac{1}{\sqrt{n}} B_t, \quad t \in [0, 1]; \quad (\Theta, d) = (L^2[0, 1], \|\cdot\|_2)$$

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*Ghosal & van der Vaart 2007:*

If there exist  $\Theta_n \subset \Theta$  s.t. for  $\epsilon_n$  with  $n\epsilon_n^2 \geq 1$

- $\mu(\theta \in \Theta : \|\theta - w_0\|_2 \leq \epsilon_n) \geq e^{-cn\epsilon_n^2}$
- $\frac{\mu(\Theta \setminus \Theta_n)}{\mu(\theta \in \Theta : \|\theta - w_0\|_2 \leq \epsilon_n)} = o(e^{-n\epsilon_n^2})$ .
- $\sup_{\epsilon > \epsilon_n} \log N(\epsilon/8, \Theta_n, \|\cdot\|_2) \leq n\epsilon_n^2$

Then posterior contracts at rate  $\epsilon_n$  wrt  $\|\cdot\|_2$  at  $w_0$ .

# Outline

- 1 Posterior contraction with Gaussian priors
- 2 Posterior contraction for  $p$ -exponential priors
- 3 Contraction rates for white noise model

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# Contraction with Gaussian priors

*van der Vaart & van Zanten (2008):*

For appropriate  $\epsilon_n$

there exists  $X_n \subset X$  s.t.

$$\blacktriangleright \mu(\|u - w_0\|_X < 2\epsilon_n) \geq e^{-n\epsilon_n^2}$$

$$\blacktriangleright \mu(X \setminus X_n) \leq e^{-Cn\epsilon_n^2}$$

$$\blacktriangleright \log N(\epsilon_n, X_n, \|\cdot\|_X) \leq Cn\epsilon_n^2$$

# Contraction with Gaussian priors

*van der Vaart & van Zanten (2008):*

For  $\epsilon_n$  satisfying

$$\phi_{w_0}(\epsilon_n) \leq n\epsilon_n^2 \quad \text{with} \quad \phi_w(\epsilon) := \inf_{h \in H: \|h-w\|_X \leq \epsilon} \frac{1}{2} \|h\|_H^2 - \log \mu(\epsilon B_X)$$

there exists  $X_n \subset X$  s.t.

- ▶  $\mu(\|u - w_0\|_X < 2\epsilon_n) \geq e^{-n\epsilon_n^2}$
- ▶  $\mu(X \setminus X_n) \leq e^{-Cn\epsilon_n^2}$
- ▶  $\log N(\epsilon_n, X_n, \|\cdot\|_X) \leq Cn\epsilon_n^2$

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Given  $X$  and regularity of  $w_0$ , one can calculate  $\epsilon_n$

For appropriate models, rate  $\epsilon_n$  is posterior contraction rate



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## $p$ -exponential priors

- $\mu$  law of  $(\gamma_\ell \xi_\ell)_\ell$  in  $(\mathbb{R}^\infty, \mathcal{B}(\mathbb{R}^\infty))$ , where

$\gamma_\ell \rightarrow 0$  is a deterministic positive sequence

$\xi_\ell \sim c_p \exp(-\frac{|x|^\rho}{\rho})$ , i.i.d.  $p \in [1, 2]$

e.g.  $(\gamma_\ell) \in \ell_2$  implies  $\mu(\ell_2) = 1$

- For  $X \subset \mathbb{R}^\infty$  a separable Banach space with Schauder basis  $\{\psi_\ell\}$ ,  $\mu$  can be identified with a measure on  $X$  through

$$u(x) = \sum_{\ell=1}^{\infty} \gamma_\ell \xi_\ell \psi_\ell(x)$$

decaying properties of  $\gamma_\ell$

and regularity of  $\psi_\ell$  determine regularity of  $u$

e.g.  $(\gamma_\ell) \in \ell_2$  and  $\{\psi_\ell\}$  o.n. basis for  $X = L^2$  implies  $\mu(L^2) = 1$

- Space of admissible shifts of  $\mu$  is

$$Q := \{h \in \mathbb{R}^\infty : \sum_{\ell=1}^{\infty} \frac{h_\ell^2}{\gamma_\ell} < \infty\}.$$

- For  $h \in Q$

$$\begin{aligned} \frac{d\mu(\cdot - h)}{d\mu}(u) &= \lim_{N \rightarrow \infty} \prod_{\ell=1}^N \frac{f_p(u_\ell - h_\ell)}{f_p(u_\ell)}, \quad \left(f_p(x) := c_p e^{-|x|^p/p}\right) \\ &= \lim_{N \rightarrow \infty} e^{\frac{1}{p} \sum_{\ell=1}^N \left(|\frac{u_\ell}{\gamma_\ell}|^p - |\frac{u_\ell - h_\ell}{\gamma_\ell}|^p\right)}. \end{aligned}$$

*Shepp (1965); Kakutani (1948); or see monograph Bogachev (2010)*

- Let  $Z := \{h \in \mathbb{R}^\infty : \|h\|_Z := \sum_{\ell=1}^{\infty} |\frac{h_\ell}{\gamma_\ell}|^p < \infty\}$ ,
- $Z \subset Q$  for  $p \in [1, 2]$ ,  $\mu(Z) = \mu(Q) = 0$ .
- For  $p = 2$ ,  $Z = Q = H$
- When  $\mu$  defined on function space  $X$ ,  
 $Z \subset Q$ , both compactly embedded in  $X$

- for  $h \in Z$

$$\mu(\epsilon B_X + h) \geq e^{-\frac{1}{p} \|h\|_Z^p} \mu_0(\epsilon B_X)$$

$$\text{using } \frac{d\mu(\cdot - h)}{d\mu}(u) = \lim_{N \rightarrow \infty} \exp\left(\frac{1}{p} \sum_{\ell=1}^N \left| \frac{u_\ell}{\gamma_\ell} \right|^p - \left| \frac{h_\ell - u_\ell}{\gamma_\ell} \right|^p\right)$$

*Agapiou, D & Helin (2020)*

Agapiou, D & Helin (2020):

For  $\epsilon_n > 0$  with

$$\phi_w(\epsilon_n) = \inf_{h \in Z: \|h - w_0\|_X \leq \epsilon_n} \frac{1}{2} \|h\|_Z^p - \log \mu(\epsilon_n B_X) \leq n\epsilon_n^2$$

for any  $C > 0$  there exists  $X_n \subset X$  and  $R > 0$  s.t.

- ▶  $\mu(\|u - w_0\|_X < 2\epsilon_n) \geq e^{-n\epsilon_n^2}$
- ▶  $\mu(X \setminus X_n) \leq e^{-Cn\epsilon_n^2}$
- ▶  $\log N(4\epsilon_n, X_n, \|\cdot\|_X) \leq RCn(\epsilon_n \vee \tilde{\epsilon}_n)^2$

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Two-level Talagrand's inequality – 1994,  $\forall M > 0$

$$\mu(A + M^{\frac{p}{2}} B_Q + MB_Z) \geq 1 - \frac{1}{\mu(A)} \exp(-cM^p)$$

$$X_n = \epsilon_n B_X + M_n^{\frac{p}{2}} B_Q + M_n B_Z, \quad M_n \asymp (n\epsilon_n^2)^{\frac{1}{p}}.$$

Approximating  $Q$  by  $Z$ :  $X_n \subset 2\epsilon_n B_X + \bar{M}_n B_Z$

Let  $h_1, \dots, h_N \in \bar{M}_n B_Z$  be  $2\epsilon_n$ -apart in  $\|\cdot\|_X$

$$1 \geq \sum_{j=1}^N \mu(\epsilon_n B_X + h_j) \geq \sum_{j=1}^N e^{-\frac{\|h_j\|_Z^p}{p}} \mu(\epsilon_n B_X) \geq N e^{-\frac{\bar{M}_n^p}{p}} e^{-\phi_0(\epsilon_n)}.$$

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## White noise model

$$Y_t^{(n)} = \int_0^t w_0(s) ds + \frac{1}{\sqrt{n}} B_t, \quad t \in [0, 1]$$

- $X = L^2[0, 1]$
- $\mu$  :  $p$ -exponential,  $p \in [1, 2]$ ,  $\gamma_\ell = \ell^{-\frac{1}{2}-\alpha}$ ,  $\alpha > 0$  ( $\alpha$ -regular)
- $w_0 \in B_q^\beta$ , where

$$B_q^\beta := \left\{ u \in \mathbb{R}^\infty : \sum_{\ell=1}^{\infty} \ell^{q\beta + \frac{q}{2} - 1} u_\ell^q < \infty \right\}$$

## Rates for white noise model

$$\phi_w(\epsilon_n) = \inf_{h \in Z: \|h - w_0\|_X \leq \epsilon_n} \frac{1}{2} \|h\|_Z^p - \log \mu_0(\epsilon_n B_X) \leq n \epsilon_n^2$$

with  $Z = B^{\alpha + \frac{1}{p}}$ .

- We find the fastest  $\epsilon_n$  s.t. both

$$\inf_{h \in Z: \|h - w_0\|_X < \epsilon_n} \|h\|_Z^p \leq n \epsilon_n^2$$

and

$$-\log \mu(\epsilon_n B_X) \leq n \epsilon_n^2$$

# Rates for white noise model

Agapiou, D & Helin (2020):

$w_0 \in B_q^\beta$ ;  $\mu$   $p$ -exponential and  $\alpha$ -regular

- For  $q \geq 2$

$$\epsilon_n = \begin{cases} n^{-\frac{\beta}{1+2\beta+p(\alpha-\beta)}}, & \text{if } \alpha \geq \beta, \\ n^{-\frac{\alpha}{1+2\alpha}}, & \text{if } \alpha < \beta. \end{cases}$$

- For  $q < 2$  and  $p \leq q$ ,

$$\epsilon_n = \begin{cases} n^{-\frac{2\beta q + q - 2}{4(q-1) + 4\beta q + 2pq(\alpha-\beta)}}, & \text{if } \alpha \geq \frac{\beta p - 1 + a}{2p}, \\ n^{-\frac{\alpha}{1+2\alpha}}, & \text{if } \alpha < \frac{\beta p - 1 + a}{2p}. \end{cases}$$

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- for  $q \geq 2$ , for  $\beta = \alpha$  we get minimax rates  $n^{-\frac{\beta}{1+2\beta}}$

- for  $q < 2$ , priors with  $p < 2$  do better than Gaussian;

Gaussian with linear estimators achieve  $n^{-\frac{\beta-\gamma/2}{1+2\beta-\gamma}}$ ,  $\gamma := (2-q)/q$ .

- Rescaled priors for white noise model:

$$\bar{\mu} : \text{law of } (\lambda\gamma_\ell)_\ell, \quad \gamma_\ell = \ell^{-\frac{1}{2}-\alpha}$$

choosing  $\lambda_n$  appropriately gives

minimax rate for  $q = p < 2$  and  $\alpha = \beta - \frac{1}{p}$

minimax rate up to logarithmic factors

for  $p < q < 2$  and  $\alpha = \beta - \frac{1}{p}$

- Density estimations

Similar techniques give contraction rates,  
but they are sub-optimal